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Abstract: - Visual analysis of the physiological signals recorded at sleep time constitutes a heavy task for the clinician. In fact data quantity to be analyzed, generally corresponding to eight hours of recordings studied per 30s epochs, as well as the complexity of this analysis require a significant time. The objective of our work is to propose a tool for automatic analysis and decision-making based on artificial neural networks (ANN). In this paper, we present an outline of this tool and we propose to compare human and ANN performances on a simple case of vigilance states labeling. The first difficulty consists of the choice of representation for the physiological signals and in particular the electroencephalogram (EEG) which is regarded as the principal indicator of sleep stages. Once the representation is adopted, the following step is the design of the optimal ANN by a training and validation process on data set of a healthy adult. The results obtained, on average 76% of agreement between the expert and the ANN for six stages of vigilance, encourage us to look further into the study of these problems at the levels of modeling and design to improve the performances of our tool.

Key-Words: - Artificial Neural Networks, Decision-making, Electroencephalogram Modeling, Sleep Analysis

1 Introduction

Designing an automatic tool to interpret electroencephalogram (EEG) signals and recognize such elements as vigilance states, pathologies of sleep or other phenomena related to Brain-Computer Interface (BCI) is of high interest but has no satisfactory solution today. In [1], we have tried to better understand the reasons why this task is so difficult, comparing human expertise and automatic analysis. On one hand, we have shown that they are difficult to compare because they don't work exactly on the same data. On the other hand, we have underlined the multi-level and multi-criteria characteristics of human expertise, difficult to reproduce with classical data analysis tools. Concerning this latter point, we have proposed that Artificial Neural Networks (ANN) could be good candidate for such a task, since they can be used for signal processing, multi-modal analysis as well as decision-making and we are currently working at these various levels with ANN. Concerning the former point, it was important for us to compare human and ANN performances in similar conditions, which is rarely the case as stated in [1]. This is the topic of this paper in the framework of a sleep analysis study.

2 Sleep Analysis

In the clinical routine, the study of the sleep consists of the acquisition and the recording during one sleep night of a physiological signals set (polysomnography), followed by a visual analysis to establish the diagnosis. This study is mainly based on three signals: electroencephalogram (EEG), electrooculogram (EOG) and electromyogram (EMG). EEG signal reflects the cerebral electric activity, it is recorded with electrodes set on the scalp. The site of the electrodes is defined according to the nomenclature of the system 10-20 adopted by the majority of the clinical neurophysiology laboratories. EOG signal represents the ocular activity and is recorded with electrodes placed on the circumference of the eyes orbits. EMG signal corresponds to the muscular activity recorded by an electrode placed on the chin [2].

2.1 Visual Analysis

The visual analysis consists in detecting the variations of the EEG, the EOG and the EMG during the night. These changes define the vigilance states which are the awakening and the five stages of the sleep: stage 1, stage 2, stage 3, stage 4 and the rapid eye movement sleep (REM) [3]. Each state is characterized by the presence of one or more indicators corresponding to elementary activities and several graphical elements in the recorded signals. According to these indicators and by observing the standard rules by Rechtschaffen and Kales [4] the clinician associates to one epoch (a temporal unit used as reference, generally of 30s) a label corresponding to the estimated physiological state. The grouping-together of the all night sleep labels constitutes the hypnogram. It is

a graphical representation of the various sleep stages organization during the night and makes it possible to have an overall representation of the sleep architecture. The hypnogram obtained and the statistical data computed on the sleep stages will constitute a report which will be the base of the clinical decision-making.

Indicator	Definition	State
Alpha wave	Frequency of 8 to 12Hz	Awake
Theta wave	Frequency of 4 to 8Hz	Stage 1, 2 and REM
Delta wave	Frequency of 0.5 to 4 Hz	Stage 3 and 4
K complex	transient slow waves	Stage 2

Table 1: main EEG indicators.

The difficulty of the visual analysis lays in several aspects. Firstly, the quality of the signals recorded depends on the quality of the electrodes used and their setting (on the scalp or elsewhere). A bad setting can produce noise and artifacts, due to bad contacts or patient movements and complicate the signal interpretation. Secondly, the rules for visual interpretation themselves can be evoked. Indeed these rules are based on the visual detection of some particular waves and some graphical elements present in the physiological signals and in particular the EEG (Table 1). In addition to the Alpha, Theta and Delta waves, main EEG indicators to discriminate vigilance states, the bands of sleep also gather the Sigma waves (from 12 to 16 Hz) and the Beta waves (from 16 to 32 Hz).

The detection of these indicators is more or less difficult according to the clinician and its experience. Moreover it is frequent that these elements overlap or are affected by artifacts. The rules of visual analysis include a part of subjectivity, for example the presence of the Delta waves in more than 50% of the time period, which can lead to discordances in the labeling between clinicians. A study shows that the rate of agreement between clinicians in the same laboratory is about 95% [5]. In addition to the difficulties noted previously, we should not forget the time spent by this analysis (to label or score one night of 8h of sleep, per 30s epochs, a few hours of expert work is required on average).

2.2 Automatic Analysis

The development of automatic sleep analysis systems, intensified by the technological improvements in the micro-processing field, gave rise to numerical polygraphs. Currently, practically all the new numerical polygraphs are equipped with an automatic sleep analyzer more or less powerful [6,7]. The interest for these systems in the sleep study services is increasing for multiple reasons among which we can mention:

- Considerable increase in the requests for recordings and the need for an automatic analysis system releasing the clinician from certain examination tasks;
- The growing number of the parameters intervening in a polygraphic recording and especially the need for quantifying and for classifying all these parameters;
- The interest to have a new vision of continuity and sleep architecture, not directly observable visually but only after signal processing like the activity with slow waves, the microstructure of the sleep, etc.

The majority of the automatic analysis systems uses as reference the visual analysis criteria of Rechtschaffen and Kales (R&K) which remain the only consensus of sleep stages classification. Thus any measurement of performance of these systems is performed compared to the visual analysis.

An automatic analysis system can be described like an association of two parts: a data part and a treatments part. The data or the parameters are a representations of the physiological signals. This representation must be faithful with regard to the characteristics of the signal and must keep its fundamental properties while bringing a simplification, without great losses, in order to facilitate the following step: the treatment. This second part is composed by the treatment algorithms which aim to associate the data information to the sleep stage.

On the data part level, the major difficulty for these systems consists of the choice of modeling of the physiological signals. Indeed the choice of modeling influences considerably the performances of the system. Various techniques of analysis are used: amplitude analysis, period analysis, spectral analysis, etc [6]. Among these techniques the spectral analysis with Fast Fourier Transform (FFT) is mainly used. This choice can be explained by the fact that the visual analysis is based primarily on the detection of some waves with particular frequencies (Table 1).

On the treatment part level, research explored a broad range of traditional techniques or resulting from the artificial intelligence techniques. Among these techniques, we will be interested here in Artificial Neural Networks (ANN) which are the subject of our study and which will be used in the following section. ANN are largely applied in neurophysiological fields like EEG analysis [8], analysis of vigilance [9], sleep analysis [10], etc.

As it was explained in the introduction part, the goal of this paper is to compare the performance of a human expert and an ANN in a simple labeling task, based on the same data and the same representation, in an experiment that we describe below.

3 Materials

3.1 Subject

This experiment used one sleep night recording of a 39 years old male adult. This subject was addressed to the service "Functional Explorations of the Nervous System" in the Sahloul Hospital, in Tunisia, for the suspicion of sleep disorder. The visual analysis as well as the report drawn up show that it is a healthy patient.

3.2 Data

The physiological signals collected on the subject are amplified, filtered, digitized (sampling frequency of 256 Hz) and finally recorded on hard disk in a format adapted to sleep polygraphy. This polygraphy contains several signals among which the expert keeps for his analysis two EEG, one EOG and one EMG.

During the visual analysis the expert bases his diagnosis primarily on the first derivation of EEG. To simplify our work we will adopt this derivation as single indicator for automatic classification. The Table 2 represents the details of the recording carried out as well as the structuration in sleep stages with the number of epochs, the duration, the percentage compared to the Total Time of Sleep (%TTS) and the percentage compared to the Total Time of Recording (%TTR). The TTS represents the cumulated duration of stages 1, 2, 3 and 4 in addition to the duration of the REM sleep. These values are obtained following the visual analysis per 30s epochs carried out by one expert. We give as an additional information the theoretical values of the percentages of the stages compared to the TTS (%TV-TTS) [3].

	Epochs	%TTS	%TV-TTS	%TTR
Awake	67	---	---	6
Stage 1	54	5	< 10	5
Stage 2	347	34	~ 50	31
Stage 3	107	10	~ 10	10
Stage 4	292	26	~ 10	26
REM	233	21	20 to 25	21
Movement	14	---	---	1
TTS	1033			
TTR	1114			

Table 2 : Stage composition.

The visual analysis is carried out per 30s epochs, which yield 1114 samples for our recording. The distribution of these epochs in sleep stages is given in the Table 2. To model the selected EEG signal and to build our database we proceeded as follows (Fig.1):

- The signal is cut per 30s periods corresponding to the visual analysis epochs;
- For each portion of the signal we calculate the spectral power by the FFT. In the obtained spectrum we keep only the frequencies included in the interval]0.5, 32Hz]. This interval corresponds to the field of variation of the physiological waves (lower than 32Hz) while eliminating the continuous component (close to 0Hz frequency);
- The spectrum is subdivided in five parts corresponding to the sleep bands (Delta=[0.5,4Hz]; Theta=]4,8Hz]; Alpha=]8,12Hz]; Sigma=]12,16Hz]; and Beta=]16,32Hz]). For each band we calculate its relative spectral power (RSP) which is equal to the ratio of the band spectral power (BSP) by the total spectral power (TSP).

$$RSP_i = \frac{BSP_i}{TSP}, i \in \{Delta, Theta, Alpha, Sigma, Beta\} \quad (1)$$

Thus each 30s epoch will be represented in our database by the five values of the RSP to which we associate a label representing the sleep stage. In this database we did not integrate the epochs scored as movement considering their low number. Finally our corpus will be composed with 1100 samples distributed in the 5 sleep stages and the awake.

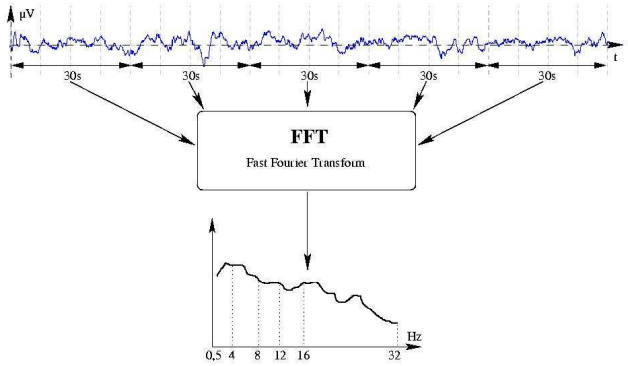

Fig.1: EEG spectral modeling.

4 Results

The experiment was carried out using a Multi-Layer Perceptron (MLP). The number of input neurons of the ANN used is fixed to 5 corresponding to the 5 values of the RSP calculated on the EEG derivation (Equation 1). The number of output neurons is fixed to 6, a neuron for each sleep stage in addition to the awake. The number of the hidden neurons is obtained after a study of several configurations, during the training process. The best success rate obtained among the various configurations tested is 76%. This rate is obtained with an ANN composed by 5 input neurons, 6 neurons in the hidden layer and 6 output neurons. Simulations are carried out by cross validation on ten random selected sets. The

confusion matrix (Table 3), result of the optimal network classification, shows that:

- Awake, stage 2, stage 4 and the REM sleep are well classified;
- Stage 1 is not recognized and it is mainly confused with the REM sleep then with stage 2;
- Stage 3 is slightly recognized and it is confused with stage 4.

The last two points can be explained by the fact that the confused stages are almost identical in the spectral composition: the Theta waves for stage 1, REM sleep and stage 2, and the Delta waves for stage 3 and stage 4 (see Table 1).

as →	Awake	S1	S2	S3	S4	REM	Success
Awake	**59**	0	0	0	5	3	88%
S1	11	**0**	17	0	2	24	0%
S2	3	1	**291**	0	21	31	84%
S3	0	0	39	**3**	52	13	3%
S4	1	0	9	2	**278**	2	95%
REM	7	0	16	0	6	**204**	88%

Table 3: Confusion matrix.

These results are also reproduced, with some differences in the numerical values, with the second EEG derivation and the same with the combinations of the two EEG derivations (10 input parameters, 5 parameters for each derivation). The combination of the two derivations does not make significant improvement to the level of the total success which passes from 76% to 77%.

5 Conclusion

The objective of this work was to advance our experience in producing a decision-making tool for sleep analysis based on Artificial Neural Networks. In this paper we presented one of our steps to better understand how we can compare human expertise and ANN decision. The presented configuration gives a 76% rate of agreement for the 6 stages. Equivalent works, using ANN and classification in 6 classes, give results which vary between 61 and 80% [8]. Even if in [1] we explain that disagreement doesn't always mean that the ANN is wrong, we are conscious, in such a simple classification stage (sleep without noise nor movement), that these results mainly show the limit of FFT modeling adopted in our study and results in the confusion between stages equivalent at the spectral level. Another choice of parameters and/or the addition of other parameters resulting from another modeling techniques like the detection of the graphical-elements and the integration of the other physiological signals may be able to improve the obtained results. It is what we are studying in ongoing work.

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